Rational Herding in Microloan Markets

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Microloan markets allow individual borrowers to raise funding from multiple individual lenders. We use a unique panel dataset which tracks the funding dynamics of borrower listings on Prosper.com, the largest microloan market in the United States. We find evidence of rational herding among lenders. Well-funded borrower listings tend to attract more funding after we control for unobserved listing heterogeneity and payoff externalities. Moreover, instead of passively mimicking their peers (irrational herding), lenders engage in active observational learning (rational herding); they infer the creditworthiness of borrowers by observing peer lending decisions, and use publicly observable borrower characteristics to moderate their inferences. Counterintuitively, obvious defects (e.g., poor credit grades) amplify a listing's herding momentum, as lenders infer superior creditworthiness to justify the herd. Similarly, favorable borrower characteristics (e.g., friend endorsements) weaken the herding effect, as lenders attribute herding to these observable merits. Follow-up analysis shows that rational herding beats irrational herding in predicting loan performance.

Key words: Rational Herding, Observational Learning, Bayesian Inference, Microloan Markets, Peer-to-Peer Lending, Prosper.com.

1. Introduction

Rapidly growing amid the recent economic turmoil, microloan markets allow individuals to borrow and lend money without financial institutions acting as intermediaries. Microloan markets differ from traditional financial markets in three distinctive ways. First, a borrower typically relies on multiple lenders, each of whom contributes a portion of the loan. Second, the social aspect of lending is prominent, as each potential lender can see how much funding others have contributed to a borrower. Third, unlike large-scale lending institutions, individual lenders may not be capable of determining a borrower's creditworthiness, which in particular refers to the borrower's default risk. These features make peer lending decisions both a possible and a salient resource that lenders can rely on in making their investment choices.

To study how these new features of microloan markets affect lending, we focus on Prosper.com, the biggest and one of the oldest microloan markets in the United States. Launched in February 2006, Prosper had enlisted 1.13 million registered members and facilitated over $256 million in loans by September 2011. Each Prosper borrower must submit a "listing" to request funding from lenders. An interested lender then chooses the amount to contribute to the listing, and this choice is publicized on the website. Peer influence is found to be a significant driver of lending on Prosper. Herzenstein, Dholakia, and Andrews (2011) document evidence of "herding" among Propser lenders, whereby borrower listings that have attracted a larger number of lenders are more likely to receive further funding.

In this paper, we explore the behavioral mechanism underlying herding among Prosper lenders. In particular, we ask whether herding is irrational or rational. *Irrational herding* occurs when lenders passively mimic others' choices, refer to others' decisions as a descriptive social norm, or follow well-funded and hence salient listings (Croson and Shang 2008; Simonsohn and Ariely 2008). *Rational herding*, on the other hand, happens as a result of *observational learning* among lenders (Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992). The premise of observational learning is as follows. Lenders are uncertain about the creditworthiness of a borrower. However, each lender might receive a private signal of the borrower's creditworthiness, for example, by processing the listing information based on her personal experience, or by acquiring information through affiliations with the borrower in Prosper user groups. Lenders can thus make rational Bayesian inferences of a borrower's creditworthiness from observing others' lending decisions.

It is important to distinguish between irrational and rational herding. Which behavioral mechanism dominates affects critically what strategies the supply side should undertake to harness the power of herding. If irrational herding dominates, it pays to build early momentum since herding will be self-reinforcing (Simonsohn and Ariely 2008). If rational herding dominates, however, the effects of momentum-building efforts are more nuanced. Rational observational learners care not only about the presence of herding, but also the various reasons that have given rise to the herd. Therefore, momentum-building efforts may dilute the quality signal contained in the herd, as observational learners attribute herding to external efforts rather than to intrinsic quality.

To understand how herding operates on Prosper, we collect a unique panel dataset of Prosper listings posted from the website's inception in February 2006 through September 2008. For each listing, the dataset contains the amount requested, interest rate offered, the borrower's credit grade, debt-to-income ratio, number of friend endorsements, Prosper group membership, homeownership, listing date, and the progression of the listing's funding status over its duration, which is typically seven days.

Empirical identification of rational herding proceeds in three steps. First, we control for *unobserved heterogeneity* across listings and *payoff externalities* among lenders as potential confounding factors of herding. Specifically, the amount of funding a listing receives each day may be sequentially correlated simply because unobserved (by the researcher) listing attributes or contextual factors affect all lenders funding the same listing (Manski 1993; Villas-Boas and

Winer 1999; Chintagunta 2001; Kuksov and Villas-Boas 2008). Meanwhile, payoff externalities occur when a lender's return from funding a listing depends on others' lending behaviors (Katz and Shapiro 1985). In particular, listings that fail to receive the full amount requested do not turn into loans. Although lenders' contributions are refunded in this case, they incur opportunity costs of time and investment. Therefore, even without herding incentives, lenders may prefer a well-funded listing just because it is more likely to materialize into a loan.

The panel structure of the data allows us to capture unobserved listing heterogeneity with listing fixed effects, and identify peer influence among lenders based on the within-listing variation in the amount of funding across time (Wooldridge 2002). Meanwhile, we exploit variations in a listing's percentage funded to capture the effect of payoff externalities: before a listing is fully funded, a lender may assess its chance of becoming a loan from its existing funding level; after a listing is fully funded, this concern no longer explains the remaining sequential correlation in lending. Using these identification methods, we confirm the existence of herding among lenders—the amount of funding a listing has received remains a significant indicator of its future funding after controlling for unobserved listing heterogeneity and payoff externalities.

We then focus on distinguishing between irrational and rational herding by investigating whether the herding effect is moderated by observable listing attributes. If lenders are simply duplicating others' investment decisions or are drawn by saliency, they tend to ignore auxiliary listing characteristics. Indeed, Simonsohn and Ariely (2008) find that irrational eBay bidders herd into auctions with many existing bids but ignore the fact that it is the lower starting prices that have attracted these bids. In contrast, if lenders are rational observational learners, the inferences they draw from existing funding should depend on listing attributes. We develop a theoretical model to illustrate this identification strategy. The idea is as follows. Consider two equally well-funded listings with identical attributes except that listing 1 shows an AA credit grade while listing 2 reports a high-risk grade. A rational lender would then partly attribute listing 1's funding to its credit grade, but reason that "there must be something really good about listing 2" such that other lenders are willing to invest despite its poor credit grade. The incremental quality inference drawn for listing 2 should therefore be more positive.

Applying this identification strategy, we find significant evidence of rational herding on Prosper. Seemingly unfavorable listing attributes, such as poor credit grades and high debt-to-income ratios, amplify a listing's herding momentum. Apparently favorable listing attributes, such as friend endorsements and group membership, weaken the attraction of a listing's popularity. We verify the robustness of these findings using the dynamic Generalized Method of Moments (GMM) that controls for serially correlated errors; a fixed effects Poisson model that captures the truncated nature of lending while accommodating unobservable listing heterogeneity; and specifications that investigate multicollinearity, various covariates, alternative measures of herding momentum, and changes in interest rates before and after full funding.

Finally, we present corroborating evidence of rational herding by restructuring the panel data, and by exploiting auxiliary data on Prosper. In a finer-grained analysis of first-day funding dynamics, we find that lenders are less influenced by the herding momentum and by the hypothesized moderating effects of listing attributes on herding. To the extent that first-day lenders process information more independently, this finding can be interpreted as passing a "falsification test" of rational herding. We also examine the effects of a series of Prosper website redesigns and user conferences that enhance the informativeness of the Prosper lending environment. These events are found to strengthen the information content and thus the influence of the herd, an effect that is consistent with rational herding. Last but not least, we are able to measure intrinsic borrower creditworthiness from subsequent loan default rates. We find that well-funded listings are indeed less likely to default. Moreover, we compute counterfactual funding outcomes assuming irrational herding, and find irrational herding to be a weaker predictor of loan performance than rational herding.

There is a growing literature on herding. The seminal works of Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992) prove that observational learning can lead to rational herding, whereby individuals draw Bayesian inferences from, and thus duplicate, their predecessors' choices. A stream of research documents evidence of herding experimentally. Through laboratory experiments, Anderson and Holt (1997) and Çelen and Kariv (2004) directly observe the point in time when subjects join a herd. Through field experiments, Salganik, Dodds, and Watts (2006) find that music buyers seek frequently downloaded songs; Cai, Chen, and Fang (2009) find that restaurant customers prefer popular dishes; Tucker and Zhang (2011) find that displaying click count information attracts web visitors to popular vendors, especially those who serve niche tastes. Through a natural experiment on Amazon.com that shifts the observability of peer choices, Chen, Wang, and Xie (2011) separate herding from word-of-mouth among buyers.

Another stream of research documents herding in non-experimental environments. Besides the aforementioned studies of Simonsohn and Ariely (2008) and Herzenstein, Dholakia, and Andrews (2011), Zhang (2010) finds that patients waiting for transplant kidneys are more likely to turn down a kidney after observing other patients' rejection decisions. Agrawal, Catalini, and Goldfarb (2011) find that well-funded musician-entrepreneurs on the crowdfunding website Sellaband.com tend to attract more investors, especially those far from the musicians in the offline social network. In the setting of product diffusion, Elberse and Eliashberg (2003) model the "success-breeds-success" trends in international movie markets; Golder and Tellis (2004) reinterpret the concept of product life cycle from the "informational cascades" perspective.[1]

[1] See also Cai, Chen, and Fang (2009), and Herzenstein, Dholakia, and Andrews (2011) for discussions of the herding literature.

Our study contributes to the herding literature by highlighting the distinction between irrational and rational herding. Many works in this area either focus on demonstrating the existence of herding or implicitly assume a behavioral basis for herding. One exception is Simonsohn and Ariely (2008), who find that eBay bidders' pursuit of popular auctions is irrational. This finding complements the notion that the auction environment on eBay might induce irrational tendencies such as "competitive arousal" and "inattention" (see Malmendier and Lee 2011 for a review of irrational behaviors in auction markets). In contrast, the focus of Prosper is not on auctions, but on helping lenders find good investment opportunities in a cooperative, community-based environment (Herzenstein, Dholakia, and Andrews 2011). Therefore, Prosper lenders may have the motivation and opportunity to make more rational decisions. Our panel data allow us to empirically evaluate this hypothesis. We continue in the next section with an overview of microloan markets and a description of the Prosper setting.

2. Background and Data

2.1. Overview of Microloan Markets

Microloans date back to 300 A.D. in China, where the first private credit union, called "Lun Hui," was founded.[2] In Japan, the same microloan idea was called "Minyin," in Egypt "Gamey," and in Brazil "Consorcio." For centuries, small groups of people all over the world have been coming together to borrow and lend over brick-and-mortar microloan markets.

In the past decade, web-based micro-lending (also called peer-to-peer lending, social lending, or crowdfunding) has quickly gained popularity thanks to growing economies of scale, reduced transaction time, and decreased transaction costs on the Internet. This momentum in growth has been further accelerated by the recent credit crunch, which drives individual borrowers to microloan markets as banks tighten their lending criteria. The total amount of outstanding microloans are projected to reach $5 billion by 2013.[3]

Founded in 2001, and subsequently acquired by Virgin Money in October 2007, Circle Lending was one of the pioneering microloan websites. Since then, more than twenty sites have emerged around the globe. Table A1 of the Online Appendix (posted on www.SSRN.com) presents an overview of microloan websites worldwide at the time of our data collection. Among these websites, Prosper, Zopa, Kiva, Lending Club, and Virgin Money have evolved as top microloan platforms.[4]

[2] Bouman, F.A.J., "ROSCA: On the Origin of the Species," *Savings and Development*, XIX, No. 2, 1995, p. 129.

[3] Source: "Peering Into the Peer-to-Peer Lending Boom," *Daily Finance*, February 13, 2011.

[4] Another major microloan platform is Sellaband.com, which helps musicians raise financing from individual investors. See Agrawal, Catalini and Goldfarb (2011) for a study of how geography affects crowdfunding on Sellaband.

2.2. Prosper.com

Opened to the public in February 2006, Prosper.com has rapidly grown into the largest microloan market on the Internet. By September 2011, Prosper had attracted 1.13 million registered members and facilitated over $256 million in loans.[5]

Lending and borrowing on Prosper proceed as follows. When a borrower requests a loan, she must create a listing, which specifies the amount she would like to borrow (between $1,000 and $25,000 as required by Prosper), the maximum interest rate that she is willing to pay (later referred to as the "borrower rate"), and the duration, in number of days, for the listing to remain active to receive funding. The modal duration is seven days, which accounts for about 60% of all listings. The borrower must include a written statement to describe the purpose of the loan, and provide a credit profile, which includes her debt-to-income ratio and a Prosper credit grade. A Prosper credit grade is a letter grade on a seven-point scale, ranging from AA to HR ("high risk"), which Prosper assigns based on the verified Experian Scorex PLUS credit score from the borrower's credit report. Table 1 presents Prosper credit grades and their equivalent credit scores.

Table 1 Distribution of Credit Grades across Listings

Credit Grade	Credit Score	Overall	Fully Funded	Not Fully Funded	Mean Difference	z-stat.	p-value
AA	760 and up	3.49%	17.45%	1.54%	15.91%	63.39	<.0001
A	720-759	3.36%	15.72%	1.64%	14.08%	57.09	<.0001
B	680-719	4.76%	17.73%	2.95%	14.78%	50.76	<.0001
C	640-679	7.54%	18.08%	6.07%	12.01%	33.27	<.0001
D	600-639	11.11%	15.04%	10.56%	4.48%	10.43	<.0001
E	560-599	17.58%	8.39%	18.87%	-10.48%	-20.14	<.0001
HR	520-559	51.93%	7.44%	58.15%	-50.71%	-74.26	<.0001
NC	N/A	0.22%	0.15%	0.23%	-0.08%	-1.25	0.2118
Total		100.00%	100.00%	100.00%			
Number of Observations		49,693	6,102	43,591			

Notes: This table presents the mapping between Prosper-assigned credit grades and Experian Scorex PLUS credit scores, the distribution of credit grades across all listings in the sample, and the distributions depending on whether the listing is fully funded. The p-values are based upon two-tailed tests.

Additionally, borrowers can provide a variety of optional information. They can seek endorsements from other Prosper members, typically their friends or relatives. An endorser then posts comments on the listing to support the loan request. Borrowers can also join Prosper member

[5] Source: www.prosper.com. The success of Prosper has spurred growing interest from academia. Research has investigated determinants of funding outcomes on Prosper, such as physical appearance (Ravina 2008), lender learning from hard versus soft information (Iyer et al. 2009), perceived trustworthiness (Duarte, Siegel and Young 2010), borrowers' identity claims (Herzenstein, Sonenshein, and Dholakia 2011), taste-based discrimination (Pope and Sydnor 2011), and interest rate caps (Rigbi 2011). Another stream of research examines the social network effects of Prosper, such as how friend endorsements affect loan performance (Freedman and Jin 2008), how borrowers' group affiliations relate to loan default risk (Everett 2010), how the strength and verifiability of relational network measures influence funding outcomes and loan defaults (Lin, Viswanathan and Prabhala 2011), and how participation in online communities changes lenders' risk preferences (Zhu et al. 2011).

groups and indicate their group affiliation in the listing. Prosper groups are managed by group leaders who bring borrowers to Prosper and maintain the group's presence on the site, with the objective of enhancing group members' funding success. Finally, borrowers can opt to upload a picture to the listing page.

A lender then decides whether to fund a listing and, if so, the amount to contribute and the minimum interest rate she is willing to accept.[6] When a listing is fully funded yet still active, lenders can continue to fund the listing by bidding down the interest rate. Once a listing expires and the requested amount is fully funded, a loan is created. All Prosper loans are unsecured, 36-month, fixed-rate and fully-amortizing loans. For most loans, Prosper charges a 1% servicing fee paid by borrowers. If a listing expires without full funding, all lenders receive their contributions back.

2.3. Data

We track a random sample of listings posted on Prosper from the website's inception in February 2006 through September 2008.[7] We focus on listings that specify a duration of seven days, the typical duration on Prosper. The resulting sample contains 49,693 listings. For each listing, we record a set of its attributes and monitor its funding progression, including the amount of funding it has received, the number of bids, and its current interest rate.

Table 2 presents the summary statistics for all 49,693 listings. (See Table A2 in the Online Appendix for the Pearson correlations among all variables in Table 2.) In this sample, listings request between $1,000 and $25,000, with an average of $6,713. In return, borrowers offer interest rates between 0% and 36%, with an average of 17.7%. The dummy variable *Credit_Risky* equals 1 if the listing's credit grade is either HR (high risk) or NC (unavailable).[8] Among listings in our sample, 51.9% receive an HR grade and 0.2% receive an NC grade. Another indicator of credit risks is the borrower's debt-to-income ratio, which averages 51.9%. Finally, about 99% of the listings do not receive endorsements, 26.2% of the listings come from group members, and 31.1% indicate that the borrower owns a home.

Beyond listing attributes, Table 2 also presents summary statistics on lending activities on the first day and last day of the listing period. An average listing receives 3 bids representing $296 in funding on its first day, and 6 bids totaling $555 in funding on its last day. The average

[6] The minimum amount of funding required for a bid is $25, effective July 2009.

[7] We select a random sample to track due to capacity constraints on computing. We capture newly originated listings at regular and frequent intervals to make sure the sample is representative.

[8] Although the HR grade corresponds to the lowest disclosed numerical credit scores, information disclosure theories suggest that not releasing the credit grade may signify the worst credit (e.g, Milgrom 1981). Therefore, we treat both HR and NC grades as signals of risky listings. In Section 3.5.4 we present evidence that lenders indeed perceive NC as the worst credit grade. A previous version of the paper uses the *Credit_HR* dummy variable instead of *Credit_Risky*. The results are approximately the same due to the small percentage of NC grades in the sample.

Table 2 Summary Statistics of All Listings

Variable	Mean	Std Dev	Minimum	Maximum
Listing Attributes				
Amount Requested	6,713.018	5,895.258	1,000	25,000
Borrower Rate	0.177	0.086	0	0.36
Credit_Risky (1=Yes)	0.521	0.500	0	1
Debt-to-Income Ratio	0.519	1.355	0	10.01
Endorsements	0.011	0.123	0	4
Group Member (1=Yes)	0.262	0.440	0	1
Homeowner (1=Yes)	0.311	0.463	0	1
First-Day Statistics				
Amount Funded	296.057	1,286.188	0	29,962.16
Bids	3.326	15.289	0	398
Rate	0.169	0.083	0	0.36
Last-Day Statistics				
Amount Funded	555.416	2,007.918	0	69,713.67
Bids	6.284	20.868	0	358
Rate	0.167	0.083	0	0.36
Funding Outcome				
Total Amount Funded	1,674.275	5,210.504	0	70,270.05
Total Percent Funded	0.159	0.348	0	1
Fully Funded (1=Yes)	0.123	0.328	0	1
Number of Observations	49,693			

Notes: The data for this table include a randomly selected sample of 49,693 listings posted on Prosper.com from its inception in February 2006 through September 2008. In the "First-Day Statistics" and "Last-Day Statistics" sections, "Amount Funded" is the amount received during that day; "Rate" is the interest rate that lenders would earn should the listing materialize into a loan immediately, and is measured at the end of the corresponding day. In the "Funding Outcome" section, "Total Amount Funded" is the cumulative funding each listing receives prior to expiration. It can exceed "Amount Requested" if the listing remains open for bids after it is fully funded. "Total Percent Funded" is capped at 100%.

interest rate does not seem to decline substantially; it is 16.9% at the end of the first day and 16.7% when the listing expires. The average total funding per listing is $1,674, representing 15.9% of the amount requested. Only 12.3% of listings end up receiving full funding.

Table 3 reports the above summary statistics for listings that are eventually fully funded and not fully funded, respectively. The fourth and fifth columns of Table 1 also separately present the distributions of credit grades for these two groups of listings. Although it would be premature to assess causality, fully funded listings are associated with smaller amounts requested, higher borrower rates, better credit grades, lower debt-to-income ratios, more endorsements, membership in Prosper groups, and homeownership. Furthermore, fully funded listings tend to have already demonstrated stronger momentum on the first day; they would have received, on average, 23 bids and $2,095 in funding by the end of the first day, whereas listings that fail to achieve full funding attract only 0.5 bids and $44 in funding. On average, fully funded listings end up receiving a total of $11,463, while listings that fail to be fully funded raise only $304, or 4.2% of the requested amount. All these differences are significant at the $p = 0.0001$ level. To understand the mechanism driving funding dynamics, we turn next to panel analysis.

Table 3 Summary Statistics by Funding Outcome

Variable	Fully Funded		Not Fully Funded		Mean	t-stat.	p-value
	Mean	Std Dev	Mean	Std Dev	Difference		
Listing Attributes							
Amount Requested	6,053.064	5,395.375	6,805.400	5,956.116	-752.336	-10.07	<.0001
Borrower Rate	0.207	0.079	0.173	0.086	0.034	31.14	<.0001
Credit_Risky (1=Yes)	0.076	0.265	0.584	0.493	-0.508	-122.90	<.0001
Debt-to-Income Ratio	0.285	0.785	0.552	1.413	-0.267	-22.04	<.0001
Endorsements	0.032	0.209	0.008	0.106	0.024	8.81	<.0001
Group Member (1=Yes)	0.363	0.481	0.248	0.432	0.115	17.70	<.0001
Homeowner (1=Yes)	0.492	0.500	0.286	0.452	0.206	30.49	<.0001
First-Day Statistics							
Amount Funded	2,094.880	2,959.019	44.252	379.469	2,050.628	54.07	<.0001
Bids	23.307	35.212	0.529	5.407	22.778	50.45	<.0001
Rate	0.173	0.068	0.170	0.085	0.003	4.16	<.0001
Last-Day Statistics							
Amount Funded	3,604.484	4,221.974	128.599	785.917	3,475.885	64.16	<.0001
Bids	40.725	40.575	1.462	8.758	39.263	75.34	<.0001
Rate	0.151	0.058	0.170	0.086	-0.019	-22.38	<.0001
Funding Outcome							
Total Amount Funded	11,462.597	9,740.330	304.076	1,543.134	11,158.521	89.33	<.0001
Total Percent Funded	1	0	0.042	0.158	0.958	1,265.92	<.0001
Number of Observations	6,102		43,591				

Notes: This table reports the summary statistics for listings that are fully funded and not fully funded, respectively. All variable definitions are the same as in Table 2. The p-values are based upon two-tailed tests.

3. Main Analysis

In this section, we exploit the panel structure of the data to analyze whether herding characterizes lending decisions on Prosper and, if so, whether herding is irrational or rational.

3.1. Preliminary Analysis

For each listing, we take a snapshot of the number of bids and the amount received at the end of each day, as well as the current interest rate that lenders would earn should the listing materialize into a loan immediately. These statistics are also publicized by Prosper to aid the decisions of subsequent lenders, making peer influence possible. We focus our analyses on a daily basis, because Prosper adopts “the day” as the most salient unit of measurement when it publicizes listing statistics. Nevertheless, as we will discuss later, the main results are robust when analyzed on an hourly basis.

A lender faces the following decisions: whether to lend to a borrower and, if so, the amount to contribute and the rate she is willing to accept. For most of the analysis, we focus on the amount to lend (including $0) as the ultimate measure of how a listing is received by a lender. This is because lenders essentially solve an optimal investment allocation problem among the wide selection of listings offered on Prosper. The amount to allocate to a listing reflects the marginal returns the lender anticipates to earn from this listing; the returns encompass the expected interest rate, the risks associated with the loan, etc.

We denote the amount of funding that listing j receives during its t^{th} day with y_{jt}, where $t = 1, \cdots, T$. T is the duration of a listing which equals 7 for the daily panel. The analysis of this section focuses on a listing's cumulative amount of funding as a measure of its herding momentum. This is because the cumulative amount reflects previous lenders' collective evaluations of a listing as manifested in their funding allocation decisions.[9] (Section 3.5.5 shows the robustness of the results with respect to alternative measures of herding momentum.) We use Y_{jt} to denote the cumulative amount of funding that listing j has received by the end of day t.

A naïve test of herding would be to look for sequential correlation in lending such that y_{jt} is positively correlated with the lagged cumulative amount $Y_{j,t-1}$. This test translates into a regression in which the dependent variable is y_{jt}, and the independent variables include $Y_{j,t-1}$, time-varying listing attributes X_{jt}, and time-invariant listing attributes Z_j:

$$y_{jt} = \alpha Y_{j,t-1} + X_{jt}\beta_1 + Z_j\beta_2 + e_{jt} \tag{1}$$

where $t = 2, \ldots, T$.

The time-varying listing attributes X_{jt} include the following variables: *Lag Percent Needed*, the percentage of the amount requested by listing j that is left unfunded at the end of day $t-1$; *Lag Rate*, the interest rate lenders would have earned had the listing become a loan at the end of day $t-1$, and *Lag Total Bids*, the cumulative number of bids listing j has received by the end of day $t-1$. To capture the possibility that lending concentrates on certain days of the week or certain days into a listing's duration, we further include *Day-of-Week Fixed Effects* and *Day-of-Listing Fixed Effects* in X_{jt}. Time-invariant listing attributes Z_j include *Amount Requested*, *Borrower Rate*, a *Credit_Risky* dummy, *Debt-to-Income Ratio*, *Endorsements*, a *Group Member* dummy, and a *Homeowner* dummy. We also include in Z_j a listing-specific variable *Start Day*, which indexes the date the listing is posted on Prosper, to capture the growth of Prosper and the change in loan market conditions over time.[10] The term e_{jt} is the error component. The scalar α and vectors β_1 and β_2 are parameters to be estimated.

Column (1) of Table 4 reports the GLS estimation results of Equation (1) with standard errors clustered at the listing level. The effect of *Lag Total Amount* ($Y_{j,t-1}$) is positive and significant. However, this positive sequential correlation in lending can be attributed to the following mechanisms: unobserved heterogeneity across listings, payoff externalities among lenders, irrational herding, and rational herding. Below we discuss the empirical strategy employed to disentangle these mechanisms.

[9] Although Prosper does not directly publicize a listing's cumulative funding amount, lenders can infer this amount from the amount requested and the percentage funded. Because cumulative funding amount lacks saliency, whether it affects subsequent lending decisions can be seen as a conservative test of herding.

[10] Using a continuous time variable makes it easy to present and interpret the time effect. However, the estimation results indicate a similar pattern when we include monthly dummy variables instead.

Table 4 Main Results—Rational Herding

	(1) Sequential Correlation		(2) Herding		(3) First Day		(4) Ratiaonl Herding	
Lag Total Amount	0.377	***	0.256	***			1.333	***
	(0.003)		(0.004)				(0.102)	
Lag Percent Needed (%)	-2.660	***	-0.539	***			-0.456	*
	(0.115)		(0.190)				(0.242)	
Lag Rate (%)	-1.568	**	28.936	***			35.632	***
	(0.624)		(1.053)				(1.023)	
Lag Total Bids	-16.982	***	-22.505	***			-1.733	***
	(0.224)		(0.362)				(0.438)	
Amount Requested (1,000)	12.766	***			177.183	***		
	(0.290)				(6.555)			
Borrower Rate (%)	9.428	***			-85.089	***		
	(0.609)				(4.872)			
Credit_Risky (1=yes)	-183.464	***			-321.450	**		
	(3.527)				(140.003)			
Debt-to-Income Ratio (%)	-0.141	***			-2.236	***		
	(0.012)				(0.426)			
Endorsements	98.182	***			660.580	***		
	(12.931)				(163.952)			
Group Member (1=yes)	79.493	***			208.773	**		
	(3.977)				(83.233)			
Homeowner (1=yes)	83.864	***			83.512			
	(3.579)				(71.202)			
Start Day	0.083	***			0.543	***		
	(0.007)				(0.181)			
Days before Default					0.005	***		
					(0.002)			
Lag Total Amount * Lag Percent Needed (%)			0.005	***			0.002	***
			(5.3E-05)				(6.0E-05)	
Lag Total Amount * Amount Requested (1,000)							0.019	***
							(2.1E-04)	
Lag Total Amount * Borrower Rate (%)							0.022	***
							(1.9E-04)	
Lag Total Amount * Credit_Risky							0.214	***
							(0.012)	
Lag Total Amount * Debt-to-Income Ratio (%)							1.5E-04	***
							(1.0E-05)	
Lag Total Amount * Endorsements							-0.111	***
							(0.006)	
Lag Total Amount * Group Member							-0.021	***
							(0.003)	
Lag Total Amount * Homeowner							0.003	
							(0.002)	
Lag Total Amount * Lag Total Bids							-0.001	***
							(1.2E-05)	
Lag Total Amount * Start Day							-1.0E-04	***
							(6.0E-06)	
Day-of-Week Fixed Effects	Yes		Yes		Yes		Yes	
Day-of-Listing Fixed Effects	Yes		Yes		No		Yes	
Listing Fixed Effects	No		Yes		No		Yes	
Number of Observations	347,851		347,851		5,940		347,851	
Adjusted/Pseudo R-Squared	0.294		0.489		0.195		0.526	

Notes: This table reports the estimation results of what drives funding dynamics. For columns (1), (2) and (4), each observation is a snapshot of a listing taken at the end of each day, and the dependent variable is the amount of funding a listing receives during a day. For column (3), each observation is a fully funded listing that subsequently turns into a loan, and the dependent variable is the amount of funding a listing receives during its first day. GLS with standard errors clustered by listing and reported in parentheses under parameter estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.2. Identification Strategy

3.2.1. Unobserved Heterogeneity across Listings. The available data are unlikely to capture every source of heterogeneity across listings. For example, borrowers who submit a professional photo might be more likely to attract lenders, yet our data do not include a photo variable. Statistically, the error term in the previous regression can be decomposed as $e_{jt} = u_j + v_{jt}$, where v_{jt} is orthogonal to other independent variables while u_j represents unobserved listing attributes. If u_j consists of the professionalism of borrower j's photo, it will be positively correlated with both the lagged total amount $Y_{j,t-1}$ and the current incremental amount y_{jt}. This causes an "errors in variables" type of endogeneity problem in estimating the coefficient α (Villas-Boas and Winer 1999; Chintagunta 2001; Kuksov and Villas-Boas 2008).

Fortunately, the panel structure of the data allows us to capture unobserved correlations of preferences among lenders facing the same listing (Wooldridge 2002). We rewrite Equation (1) by decomposing its error term, and control for unobserved listing heterogeneity with listing fixed effects u_j:

$$y_{jt} = \alpha Y_{j,t-1} + X_{jt}\beta_1 + Z_j\beta_2 + u_j + v_{jt}. \tag{2}$$

The identification assumption is that unobservable listing heterogeneity u_j is time-invariant. This assumption is plausible in the Prosper setting as the characteristics of a borrower are unlikely to change over the duration of the listing and listing attributes are typically determined at the time of posting. (Nevertheless, in Section 3.5.1 we will account for unobservable time-varying listing heterogeneity in the form of serially correlated errors.) Based on this assumption, we identify herding using within-listing variations in the amount received each day y_{jt}, the lagged total amount funded $Y_{j,t-1}$, and other observable time-varying listing attributes in X_{jt}. The effect of time-invariant listing attributes Z_j cannot be separately estimated from listing fixed effects u_j because of the strict multicollinearity between them.

3.2.2. Payoff Externalities. Socially correlated lending decisions may have also resulted from payoff externalities among lenders (Katz and Shapiro 1985). In particular, Prosper lenders face the risk of contributing to listings that fail to achieve full funding. Such listings will not materialize into loans, and lenders will incur opportunity costs of time and investment even though their contributions are eventually refunded. Consider two listings that are otherwise identical—even in the absence of herding incentives, the listing that has received a higher amount may still be more desirable due to its greater likelihood of turning into a loan. This positive externality may lead to overestimation of the herding effect.[11]

We exploit the variation in the funding percentage of each listing to capture the impact of payoff externalities. We introduce the interaction term between *Lag Total Amount* and *Lag Percent Needed* as an independent variable in Equation (2).[12] Before a listing is fully funded, a

[11] See Huang, Ying, and Strijnev (2011) for a study that unravels the effects of network externalities and social learning in the movie industry.

[12] Suppose a listing needs \$1,000 out of a requested amount of \$2,000, and another listing needs \$1,000 out of \$20,000. The same \$1,000 might imply different chances of full funding for these two listings. Therefore, we use *Lag Percent Needed* rather than *Lag Amount Needed* to control for the risk of loan materialization. Nevertheless, a parallel set of regressions using *Lag Amount Needed* lead to qualitatively the same conclusions.

potential lender may assess the risk of loan materialization from the percentage left unfunded. As a listing gets close to being fully funded (*Lag Percent Needed* decreases), the risk component diminishes. Therefore, we expect this interaction term to be positive in the presence of payoff externalities. Moreover, we expect Equation (2) to yield a positive and significant estimate of α after controlling for this interaction term, if lenders do engage in herding.

3.2.3. Irrational versus Rational Herding. Irrational herding could also produce sequential correlation in funding across days. First, lenders might engage in simple mimicry by allocating investments according to the popularity of listings, measured by the cumulative funding they have attracted. Second, social comparison theory suggests that lenders, when uncertain about how to allocate their funds, infer from others' lending behaviors the "appropriate" amount to contribute. For example, Croson and Shang (2008) find that individuals base their amount of voluntary donations on how much others are donating.[13] Third, Prosper offers a "Sort by % Funded" option on its website, and presents the percentage funded graphically with colored bars. Such website design features are likely to make well-funded listings more salient to subsequent lenders. These behavioral processes can give rise to herding even if lenders do not engage in rational observational learning of listing quality (Bikhchandani, Hirshleifer and Welch 1992). Equation (2) in itself cannot distinguish between irrational and rational herding, because the two mechanisms may be isomorphic in determining how much funding a listing receives over time. Cai, Chen, and Fang (2009) also lament the lack of clean experimental design that separates observational learning from a mere conformity effect.

We draw on the cross-sectional variation in publicly observable listing attributes to distinguish irrational and rational herding. If lenders are simply replicating others' lending decisions, they will be irresponsive to how others have arrived at such decisions. For instance, Simonsohn and Ariely (2008) find that inexperienced eBay bidders herd into auctions with more bids yet ignore the fact that the swarm of bids results from low starting prices. However, if lenders are rational observational learners, their inferences from observing others' lending decisions should be moderated by publicly observed listing attributes. We present a micro-level theory underlying this identification strategy in the Online Appendix, and outline the intuition below.

Suppose two listings received the same amount of funding on the first day. One listing has a high-risk credit grade and the other an AA grade. From subsequent lenders' perspective, first-day lenders must have sufficiently positive private information to be willing to fund a high-risk listing. For example, they might have known through personal connection that the borrower is a trustworthy person who had a poor credit grade due to special circumstances. On the other hand, the decision to fund an AA listing seems self-explanatory, and does not necessarily

[13] In a related study, Amaldoss and Jain (2010) find evidence of "reference group effects" in a laboratory setting.

imply favorable private information on the part of first-day lenders. Therefore, a subsequent lender would make more positive *incremental* quality inference about the high-risk listing. By the same logic, we expect the quality implications of herding momentum to be accentuated by unfavorable attributes and dampened by favorable listing attributes.

To operationalize this idea, we augment Equation (2) by adding the interaction terms between the lagged total amount and publicly observable listing attributes:

$$y_{jt} = \alpha Y_{j,t-1} + X_{jt}\beta_1 + Z_j\beta_2 + Y_{j,t-1} * Z_j\beta_3 + u_j + v_{jt}. \tag{3}$$

In the case of rational herding, β_3 should take the opposite signs of listing attributes' main effects on funding amount. In theory, we could uncover the signs of these main effects by regressing first-day amount on listing attributes, whereby all the lagged independent variables are missing values. However, there may be an omitted variable problem to this approach. This is because lenders may have private signals about listing quality, by definition of observational learning. Without data on these private signals, the sign of a listing attribute from the aforementioned regression may not correctly reflect the attribute's directional effect on first-day funding amount.

We mitigate this omitted variable problem with the proxy variable approach (Wooldridge 2002). We introduce auxiliary data on actual loan performance as a proxy for lenders' private information about borrower creditworthiness, the underlying assumption being that loan performance is positively correlated with borrower creditworthiness. We regress first-day funding amount on listing attributes, together with the *Days before Default* variable, which measures the number of days since loan initiation until default (see Section 4.3 discusses loan performance in more detail). We expect a greater number of days before default to be positively associated with borrower creditworthiness and thus positively associated with first-day funding amount. Moreover, we expect the listing attributes to switch signs in their interaction terms with lagged total amount if herding is rational.

Last, depending on whether lenders engage in irrational or rational herding, the moderating effect of a listing's existing number of bids on its cumulative funding amount may be different. In the case of irrational herding, the most salient cue is how well-funded a listing is, while how many lenders contributed to this funding status is inconsequential. However, for rational observational learners, this moderating effect is important. Suppose two listings have both received \$100. Listing 1 obtained \$100 from one lender, while listing 2 received \$50 from each of two lenders. On the one hand, listing 2 has attracted more supporting votes; on the other hand, the signal strength may be weaker for listing 2 because its second lender, an observational learner herself, has already been influenced by the first lender's \$50 contribution. To capture these possibilities, we include the interaction term *Lag Total Amount* $*$ *Lag Bids* as an independent variable.

3.3. Estimation Results

3.3.1. Existence of Herding. Column (2) of Table 4 reports the GLS estimation results of Equation (2). The R^2 statistic increases to 48.9% after we control for unobservable listing heterogeneity and payoff externalities, compared with 29.4% of column (1). *Lag Total Amount* has a significant and positive main effect, which confirms the existence of herding—a listing's past funding success does help it attract more subsequent funding, even when the listing faces no risk materializing into a loan (*Lag Percent Needed* = 0). This herding result echoes the findings of Herzenstein, Dholakia, and Andrews (2011) on Prosper, and of Agrawal, Catalini, and Goldfarb (2011) on Sellaband. As expected, by omitting unobservable listing heterogeneity and payoff externalities, the herding effect as reported in column (1) is overestimated compared with column (2).

In addition, the interaction term *Lag Total Amount* ∗ *Lag Percent Needed* is positive, which suggests that payoff externalities, in the form of reducing the risks of loan materialization, do affect lending decisions as hypothesized. The effect of *Lag Rate* is positive, which is intuitive as lenders expect higher returns from higher interest rates, other things being equal. Finally, the effect of *Lag Total Bids* is negative. One interpretation is that more past bids make a listing less attractive by driving down the interest rate. Indeed, the correlation between *Lag Rate* and *Lag Total Bids* in the panel data is -0.067 ($p < 0.001$). (We will investigate the possibility of multicollinearity in Section 3.5.3.)

3.3.2. Rational Herding. Column (3) of Table 4 presents the estimated main effects of listing attributes, using the proxy variable approach discussed earlier. As expected, larger amounts of first-day funding are associated with better credit grades, lower debt-to-income ratios, more endorsements, belonging in a group, and (signals of) lower default tendency. Listings with a later *Start Day* are also associated with more funding, possibly reflecting the growth of Prosper. A larger amount requested is positively associated with the amount of funding, although the prediction is less obvious. A higher borrower rate is found to discourage funding, which could reflect the common perception that riskier borrowers offer better rates (Loten 2011). Finally, owning a home has no significant effect on funding, consistent with the finding of Herzenstein, Dholakia, and Andrews (2011). One interpretation is that homeownership has become a weaker sign of financial security since the subprime mortgage crisis.[14] Indeed, the loan performance analysis of Section 4.3 finds no significant relation between homeownership and loan default rates.

[14] For example, the fact that a homeowner has to seek funding from Prosper likely implies that this borrower has difficulty obtaining a home equity loan, which is a negative sign of credit. In a related study, Farnham, Schmidt, and Sevak (2011) use homeowners' increased transaction costs during down markets to explain the associated decline in divorce rates among homeowners.

Column (4) of Table 4 shows the GLS estimation results of Equation (3). Out of the eight interaction terms between time-invariant listing attributes and *Lag Total Amount*, seven are consistent with the rational herding prediction.[15] Specifically:

• A higher borrower rate, risky credit grade, and higher debt-to-income ratio have negative main effects on funding according to column (3). All report positive interaction effects with *Lag Total Amount*. This result supports the hypothesis that the same herding momentum signals better borrower creditworthiness if the listing has publicly observed shortcomings.

• Displaying more endorsements, being a group member, and starting the listing in more recent days have positive main effects on funding. These attributes all have negative interactions with *Lag Total Amount*. This is again consistent with the prediction that herding is less of a sign of a creditworthy borrower if lenders can attribute herding to conspicuous borrower merits.

• As discussed earlier, homeownership has no significant main effect on funding. Correspondingly, its interaction with *Lag Total Amount* is also insignificant—a listing attribute moderates lenders' interpretation of herding only if it has truly influenced the predecessors' choices.

• The only listing attribute that goes against the rational herding prediction is *Amount Requested*. One possibility is that a larger amount requested attracts more funding because more lenders can join the listing without bidding down the interest rates (Herzenstein, Dholakia, and Andrews 2011). At the same time, a larger amount requested is often associated with higher default risks—as shown in Section 4.3—and thus may serve to amplify the herding momentum much as poor credit grades do.

Besides time-invariant listing attributes, *Lag Percent Needed* has a positive and significant interaction with *Lag Total Amount*, similar to column (2). This result can also be interpreted in light of rational herding: just because a higher percentage needed discourages funding, the fact that a listing has actually attracted some lenders despite its lack of funding serves as a stronger signal of borrower creditworthiness.

Finally, the interaction term *Lag Total Amount* $*$ *Lag Total Bids* is negative, which suggests that the information content of *Lag Total Amount* declines if lenders who have contributed are themselves influenced by a larger number of predecessors. This effect echoes the theoretical literature on rational herding—as decision-makers imitate their predecessors, their own choices become less diagnostic of quality (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992).

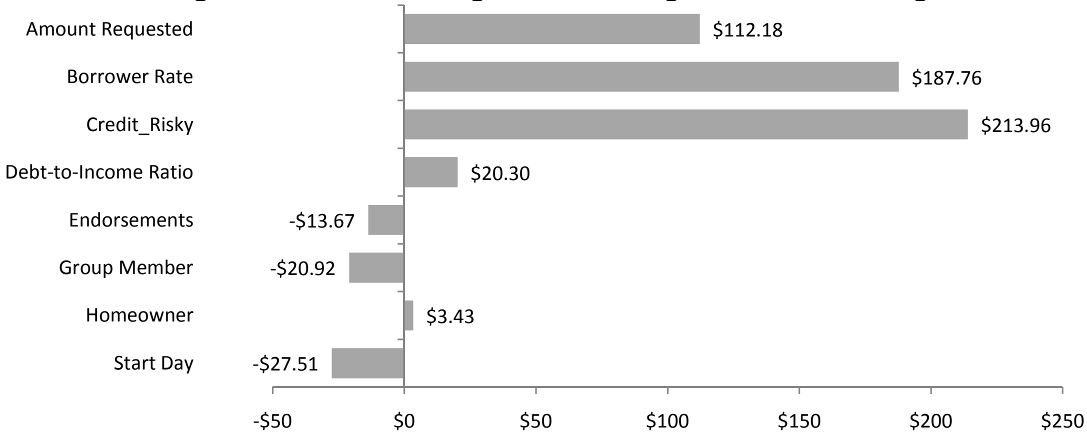
3.4. Effect Size and Managerial Implications

The estimates from columns (2) and (4) allow us to evaluate the magnitude of the herding effect. Suppose we "seed the herd" by exogenously adding $\$1,000$ of funding to a listing on

[15] We obtain the same signs when we further add the interaction between *Lag Total Amount* and *Days before Default*.

any but its last day. Column (2) suggests that, other things held constant, this funding shock will on average generate an additional \$256 for the borrower on the following day. Column (4) allows us to further assess the heterogeneous effects of this funding shock on borrowers. For each time-invariant listing attribute, we calculate the moderating effect of a one-standard-deviation increase in its value (or a zero-to-one increase for dummy variables *Credit_Risky*, *Group Member*, and *Homeowner*). Figure 1 presents the results.

Figure 1 The Moderating Effects of Listing Attributes on Herding



Notes: This figure presents the changes in the daily amount of funding following a \$1,000 funding increase on the previous day and a one-standard-deviation increase in each listing attribute (or a zero-to-one increase in dummy variables *Credit_Risky*, *Group Member*, and *Homeowner*).

The \$1,000 funding shock generates \$214 more for a risky listing on the following day compared with non-risky listings. It also brings \$112, \$188, and \$20 more for a one-standard-deviation increase in the amount requested, borrower rate, and debt-to-income ratio, respectively. On the other hand, it generates \$14, \$28, and \$21 less for a one-standard-deviation increase in endorsements and start day, and and a zero-to-one change in group membership, respectively. These moderating effects are sizable compared with the average effect of \$256.

The moderating effects of listing attributes are further amplified if we take into account the often recursive nature of herding. Suppose the \$1,000 funding shock occurs on the first day of the listing, on average it would agglomerate into an incremental funding of $(1+0.256)^6 \times \$1,000$, or \$3,926, by the end of the listing's seven-day duration, with other things held constant. Now let us consider two listings with average values on all attributes except credit grade. For the non-risky listing, the \$1,000 on day one would turn into \$1,145 on day two and \$2,253 at the end of the seventh day; for the risky listing, the numbers would be \$1,358 on day two and \$6,272 at the end of day seven. By spuriously assuming that lenders engage in irrational herding and hence ignore these moderating effects, one might grossly overestimate the effect of herding on the non-risky listing and understate the effect on the risky listing.

The above results highlight the importance of distinguishing irrational and rational herding for Prosper borrowers (and firms in general) who are interested in managing the herd. How can borrowers increase their chance of funding success? If most Prosper lenders engage in irrational herding without second-guessing the reasons behind a listing's momentum, borrowers should try to maximize their early momentum by, for example, seeking friend endorsements and joining Prosper groups. If most lenders are rational observational learners, the effectiveness of momentum-building strategies might be weakened as lenders attribute peers' patronage to borrowers' external efforts rather than their intrinsic creditworthiness. The optimal borrower strategies would therefore require careful analysis of lenders' quality inference processes.[16]

3.5. Robustness Checks

In this section, we verify whether the finding of rational herding is robust with respect to a set of alternative specifications.[17]

3.5.1. Dynamic GMM. One identification assumption behind Equation (3) is that the error terms v_{jt} are uncorrelated across time. Under this assumption, *Lag Total Amount*, its interaction terms, and all other lagged independent variables can be treated as predetermined variables that might reflect past shocks but are contemporaneously uncorrelated with v_{jt}. However, if the errors v_{jt} are serially correlated, they may be correlated with these lagged independent variables through past shocks, thus causing an endogeneity problem for estimation.

We address this concern in the dynamic GMM framework. The daily panel of this study is particularly suitable for dynamic GMM analysis because it contains a large number of cross-sectional units ($N = 347,851$) but few time periods ($T = 7$). The idea of dynamic GMM is outlined as follows (see Arellano and Bond 1991 for the technical details). By taking the first difference of Equation (3), we eliminate listing fixed effects and time-invariant listing attributes:

$$y_{jt} - y_{j,t-1} = \alpha y_{j,t-1} + (X_{jt} - X_{j,t-1})\beta_1 + y_{j,t-1} * Z_j\beta_3 + v_{jt} - v_{j,t-1}. \tag{4}$$

Since the key independent variable, $Y_{j,t-1}$ of Equation (3), is cumulative, another advantage of taking the first difference is that the corresponding independent variable in Equation (4) now only includes lagged "flow" variable $y_{j,t-1}$, which avoids the introduction of shocks from periods prior to $t-1$. Under the null hypothesis that the v_{jt} terms are serially uncorrelated, $Y_{j,t-2}$, $X_{j,t-1}$, and $Y_{j,t-2} * Z_j$, together with their longer lags, can serve as instrumental variables for Equation (4). The orthogonal relationship between the instrumental variables and the new error terms of Equation (4), $v_{jt} - v_{j,t-1}$, then constitute the moment conditions of the GMM

[16] See Miklós-Thal and Zhang (2011) for a game-theoretic analysis of optimal marketing effort choice when buyers are rational observational learners.

[17] In the interest of space, we only present robustness of the full rational herding model corresponding to column (4) of Table 4. However, the main effect of herding as shown in column (2) of Table 4 remains positive and significant in all applicable robustness checks. The main effects of listing attributes as presented in column (3) of Table 4 also retain their signs in all applicable robustness checks.

Table 5 Robustness Checks

	(1) Dynamic GMM	(2) Fixed Effects Poisson	(3) Multicollinearity Check	(4) Lag Total Amount Squared	(5) Credit Grades	(6) Time-Varying Herding
Lag Total Amount	2.710 ***	0.835 ***	1.463 ***	1.343 ***	0.499 ***	
	(0.240)	(0.026)	(0.096)	(0.102)	(0.128)	
Lag Percent Needed (%)	-2.120 ***	-2.320 ***	-0.260	-0.457 *	-0.623 **	-9.727 ***
	(0.037)	(0.123)	(0.237)	(0.242)	(0.245)	(0.223)
Lag Rate (%)	18.813 ***	31.451 ***	35.764 ***	35.585 ***	33.929 ***	34.383 ***
	(0.617)	(0.435)	(1.022)	(1.024)	(1.021)	(0.927)
Lag Total Bids	2.224 ***	-2.021 ***		-2.398 ***	-5.617 ***	3.220 ***
	(0.389)	(0.130)		(0.656)	(0.451)	(0.398)
Lag Total Amount * Lag Percent Needed (%)	0.008 ***	0.006 ***	0.002 ***	0.002 ***	0.003 ***	0.003 ***
	(1.4E-04)	(2.1E-05)	(6.0E-05)	(6.1E-05)	(6.0E-05)	(5.5E-05)
Lag Total Amount * Amount Requested (1,000)	0.023 ***	0.035 ***	0.019 ***	0.019 ***	0.020 ***	0.030 ***
	(4.7E-04)	(0.001)	(2.0E-04)	(2.2E-04)	(2.2E-04)	(2.0E-04)
Lag Total Amount * Borrower Rate (%)	0.039 ***	0.015 ***	0.022 ***	0.022 ***	0.017 ***	0.021 ***
	(4.3E-04)	(1.5E-04)	(1.9E-04)	(1.9E-04)	(2.6E-04)	(1.7E-04)
Lag Total Amount * Credit_Risky	0.113 ***	0.141 ***	0.218 ***	0.213 ***		0.109 ***
	(0.024)	(0.004)	(0.012)	(0.012)		(0.011)
Lag Total Amount * Debt-to-Income Ratio (%)	1.1E-04 ***	0.001 ***	1.5E-04 ***	1.5E-04 ***	1.7E-04 ***	1.2E-04 ***
	(2.6E-05)	(2.5E-04)	(1.0E-05)	(1.0E-05)	(1.0E-05)	(9.1E-06)
Lag Total Amount * Endorsements	-0.026 ***	-0.012 ***	-0.111 ***	-0.111 ***	-0.105 ***	-0.071 ***
	(0.010)	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)
Lag Total Amount * Group Member	-0.066 ***	-0.005	-0.020 ***	-0.021 ***	-0.025 ***	-0.008 ***
	(0.006)	(0.007)	(0.003)	(0.003)	(0.003)	(0.002)
Lag Total Amount * Homeowner	0.042 ***	0.004	0.004 *	0.004	0.016 ***	0.019 ***
	(0.006)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
Lag Total Amount * Lag Total Bids	-0.003 ***	-0.004 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.002 ***
	(5.6E-05)	(0.001)	(1.1E-05)	(2.8E-05)	(1.2E-05)	(1.1E-05)
Lag Total Amount * Start Day	-2.3E-04 ***	-2.6E-04 ***	-1.1E-04 ***	-1.0E-04 ***	-2.3E-05 ***	-9.6E-05 ***
	(3.4E-05)	(1.9E-05)	(5.6E-06)	(6.0E-06)	(6.5E-06)	(5.4E-06)
Lag Total Amount ^ 2				-4.0E-07		
				(2.8E-07)		
Lag Total Amount * Credit Grade_AA					-0.557 ***	
					(0.070)	
Lag Total Amount * Credit Grade_A					-0.469 ***	
					(0.070)	
Lag Total Amount * Credit Grade_B					-0.415 ***	
					(0.070)	
Lag Total Amount * Credit Grade_C					-0.429 ***	
					(0.070)	
Lag Total Amount * Credit Grade_D					-0.467 ***	
					(0.070)	
Lag Total Amount * Credit Grade_E					-0.286 ***	
					(0.070)	
Lag Total Amount * Credit Grade_HR					-0.184 ***	
					(0.070)	
Lag Total Amount * 2nd Day						0.594 ***
						(0.093)
Lag Total Amount * 3rd Day						0.684 ***
						(0.092)
Lag Total Amount * 4th Day						0.771 ***
						(0.092)
Lag Total Amount * 5th Day						0.870 ***
						(0.092)
Lag Total Amount * 6th Day						0.992 ***
						(0.092)
Lag Total Amount * 7th Day						1.169 ***
						(0.092)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Listing Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Listing Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	347,851	347,851	347,851	347,851	347,851	347,851
Adjusted/Pseudo R-Squared	0.370	0.514	0.526	0.526	0.529	0.611

Notes: This table reports the estimation results of a set of robustness checks. Each observation is a snapshot of a listing taken at the end of each day. The dependent variable is the amount of funding a listing receives during a day. Standard errors are clustered by listing and reported in parentheses under parameter estimates. Column (2) reports the marginal effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

procedure. Moreover, the null hypothesis of serially uncorrelated v_{jt} can be evaluated by testing for second-order serial correlation in the residuals of Equation (4).

Column (1) of Table 5 reports the estimation results when we include three lags of instrumental variables. (Other numbers of lags, from one to five, indicate similar patterns.) All independent variables except *Lag Total Bids* have the same sign as in column (4) of Table 4. The positive interaction between *Lag Total Amount* and *Homeowner* becomes significant, which suggests that borrowers' homeownership is perceived by lenders as a concern, rather than a merit, and thus serves to amplify the herding momentum. The residuals of Equation (4) exhibit significant negative first-order serial correlation of -4.51 ($p < 0.01$). This is expected as the first-differenced error $v_{jt} - v_{j,t-1}$ of Equation (4) is negatively correlated with $v_{j,t-1} - v_{j,t-2}$ by construction. However, the second-order serial correlation of the residuals is -0.03 ($p = 0.513$), which lends confidence to the assumption that the v_{jt} terms are serially uncorrelated.

3.5.2. Fixed Effects Poisson. One technical concern with Equation (3) is that the dependent variable, the daily amount that a listing receives, cannot be negative. In addition, this variable has a probability mass at zero since many listings—especially those that fail to receive the full amount requested—do not achieve any funding on a given day. To address these issues, we estimate the fixed effects Poisson model (Wooldridge 1999). The idea is that each listing's funding count (in dollars) is allowed to be drawn from a different Poisson distribution. The Poisson parameter λ_{jt} of listing j on day t is given by:

$$\log(\lambda_{jt}) = \alpha Y_{j,t-1} + X_{jt}\beta_1 + Z_j\beta_2 + Y_{j,t-1} * Z_j\beta_3 + u_j. \tag{5}$$

Column (2) of Table 5 reports the estimated marginal effects. Compared with column (4) of Table 4, all variables retain the same sign, except that the interaction between *Lag Total Amount* and *Group Member* becomes insignificant.[18] This result ensures that most of the findings reported so far are not driven by the linearity of the model. Therefore, in the remaining analysis we will report GLS estimation results for the ease of interpreting the interaction effects (Ai and Norton 2003). Correspondingly, we will refer to the GLS specification in column (4) of Table 4 as the "main model."

3.5.3. Multicollinearity. Some independent variables in the main model might be correlated. As a test for multicollinearity, Table A3 of the Online Appendix reports the variance inflation factors (VIF's) of these independent variables. All VIF's are below the conventional cutoff of 10 (Hair et al. 2009), the highest being 9.125 on *Lag Total Bids*. This could be because the volume of bids and the amount of funding are highly correlated.

[18] The deviance chi-square is used to adjust for overdispersion. The interaction *Lag Total Amount* $*$ *Group Member* is significant at the $p = 0.1$ level if the Pearson chi-square is used instead. We report the conservative result.

To investigate whether multicollinearity affects the finding of rational herding, we drop *Lag Total Bids* from the main model. Column (3) of Table 5 reports the results. All other variables retain their signs, and remain close in both significance and magnitude to their counterparts in the main model.

Extending our investigation, we estimate the main model except that we introduce the interaction terms one by one. Table A4 of the Online Appendix reports the results. *Lag Total Amount* $*$ *Homeowner* becomes significant at the $p = 0.05$ level, again suggesting that a borrower's homeownership may be a bad sign of creditworthiness. In addition, *Lag Total Amount* $*$ *Start Day* becomes positive and significant. However, all other interaction terms retain their sign and significance, suggesting that the finding of rational herding does not seem to be driven by multicollinearity.

3.5.4. Additional Covariates. Column (4) of Table 5 investigates whether the moderating effect of listing attributes on *Lag Total Amount* is an artifact of diminishing returns from *Lag Total Amount* or listing attributes. To do so, we introduce a squared term of *Lag Total Amount* into the main model. (We can also add the squared terms of the listing attributes but they are not separately estimated from listing fixed effects.) Reassuringly, the squared term of *Lag Total Amount* is insignificant, and all other variable estimates remain close to their counterparts in the main model.

Column (5) permits a closer look at the separate effects of the full range of credit grades. Relative to the dropped NC grade (meaning that the borrower's credit grade is unavailable), all other grades exhibit a significant negative interaction effect with *Lag Total Amount*. This result suggests that lenders treat NC as the worst credit grade, consistent with the prediction of information disclosure theories (e.g, Milgrom 1981). Moreover, the better the grade, the more negative the interaction effect in general. This pattern reinforces the conclusion that lenders engage in rational herding: the better the credit grade, the less informative is the herd as a sign of creditworthy borrowers.

We also expect the effect of rational herding to vary by the days elapsed into a listing's duration. This effect likely increases as time progresses, since a listing's cumulative funding reflects more lenders' valuations of this listing. Moreover, it is plausible that lenders with better private knowledge about a listing act early, while those with less private information choose to wait and base their decisions on peers' choices (Agrawal, Catalini, and Goldfarb 2011). To test these time-varying effects, we introduce the interaction terms between *Lag Total Amount* and the day-of-listing dummy variables into the main model. Column (6) reports the results. Indeed, the impact of *Lag Total Amount* monotonically increases from day two to day seven.

3.5.5. Alternative Measures of Herding Momentum. Although a listing's cumulative funding amount is a good measure of herding momentum in theory, Prosper saliently publicizes the percentage of funding a listing has achieved, and the number of bids a listing has attracted. Also, lenders can easily gain an impression of the average amount contributed by other lenders, or the amount a listing received on the previous day. Therefore, lenders might rely on these alternative cues to assess the strength of the herd. To capture this possibility, we estimate the main model but replace *Lag Total Amount* with *Lag Percent Funded* (capped at 100% to be consistent with Prosper's web display practice), *Lag Total Bids*, *Lag Average Amount*, and *Previous Day Amount*, respectively. Correspondingly, we remove *Lag Total Bids* as a separate control. We also drop *Lag Percent Needed* when *Lag Percent Funded* is used to measure herding momentum because of perfect collinearity between these two variables.

Table 6 Alternative Measures of Herding Momentum

	(1) Momemtum = Lag Percent Funded	(2) Momemtum = Lag Total Bids	(3) Momemtum = Lag Avg. Amount	(4) Momemtum = Prev. Day Amount
Momentum	97.775 ***	220.167 ***	131.411 ***	3.398 ***
	(5.996)	(9.113)	(4.415)	(0.231)
Lag Percent Needed (%)		-8.843 ***	-0.859 ***	4.070 ***
		(0.216)	(0.172)	(0.153)
Lag Rate (%)	34.253 ***	38.642 ***	31.164 ***	33.364 ***
	(1.059)	(1.029)	(1.071)	(1.045)
Momentum * Lag Percent Needed (%)	0.393 ***	0.470 ***	-0.026 ***	0.002 ***
	(0.005)	(0.005)	(0.001)	(9.0E-05)
Momentum * Amount Requested (1,000)	0.620 ***	1.086 ***	0.154 ***	0.012 ***
	(0.016)	(0.016)	(0.008)	(3.7E-04)
Momentum * Borrower Rate (%)	0.884 ***	1.947 ***	0.386 ***	0.032 ***
	(0.011)	(0.017)	(0.010)	(4.2E-04)
Momentum * Credit_Risky	3.904 ***	25.432 ***	0.096	0.250 ***
	(0.352)	(1.331)	(0.164)	(0.024)
Momentum * Debt-to-Income Ratio (%)	0.022 ***	0.036 ***	0.003 ***	2.2E-04 ***
	(0.001)	(0.001)	(4.5E-04)	(2.6E-05)
Momentum * Endorsements	-4.092 ***	-11.894 ***	-1.215 ***	-0.099 ***
	(0.325)	(0.475)	(0.307)	(0.010)
Momentum * Group Member	-1.161 ***	-0.707 ***	-1.907 ***	-0.083 ***
	(0.177)	(0.246)	(0.115)	(0.006)
Momentum * Homeowner	-0.027	0.514 **	-0.171	0.027 ***
	(0.156)	(0.213)	(0.114)	(0.006)
Momentum * Start Day	-0.007 ***	-0.016 ***	-0.008 ***	-2.3E-04 ***
	(3.4E-04)	(0.001)	(2.6E-04)	(1.3E-05)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Listing Fixed Effects	Yes	Yes	Yes	Yes
Listing Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	347,851	347,851	347,851	347,851
Adjusted/Pseudo R-Squared	0.497	0.523	0.472	0.493

Notes: This table reports the estimation results when we adopt alternative measures of listing momentum. Each observation is a snapshot of a listing taken at the end of each day. The dependent variable is the amount of funding a listing receives during a day. In column (2), listing momentum as measured by *Lag Percent Funded* is capped at 100%. GLS with standard errors clustered by listing and reported in parentheses under parameter estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 presents the estimation results. The rational herding interpretation continues to hold with these alternative measures of herding momentum. The same herding momentum signifies greater borrower creditworthiness if it is achieved in spite of the borrower's conspicuous shortcomings, and serves as a weaker sign if it can be partly attributed to the borrower's obvious merits. In particular, the results in column (3) suggest that lenders are not passively imitating how much others are contributing, as social comparison theory might suggest (Croson and Shang 2008).[19] They seem instead to interpret others' amount of lending in a rational way, drawing upon listing attributes to fine-tune their inferences.[20]

3.5.6. How Herding Affects Interest Rates. Finally, interest rate dynamics may provide a robustness check of rational herding form a different angle. Since lenders' decisions are eventually governed by risk-return tradeoffs, we expect lenders' willingness to accept a lower interest rate to reflect higher perceived borrower creditworthiness. In the presence of herding, we therefore expect lower interest rates on a well-funded listing. If herding is rational, we further expect the signs of the interaction terms to be the opposite of those in the main model; favorable (unfavorable) listing attributes should weaken (strengthen) the appeal of a well-funded listing, and hence increase (decrease) the interest rates.

Since Prosper lenders tend to bid down interest rates only after a listing becomes fully funded, we focus on the part of the panel data where the listings have reached full funding status. Correspondingly, *Lag Percent Needed* and its interaction with *Lag Total Amount* drop out of the estimation. We treat a listing's interest rate (%) at the end of each day as the dependent variable. Table A5 of the Online Appendix reports the results in columns (1) and (2). The main effect of *Lag Total Amount* on interest rates is negative and significant, consistent with the herding hypothesis. Moreover, although some interaction terms lose significance, all the significant interactions have opposite signs of those in column (4) of Table 4, consistent with the rational herding hypothesis. As a falsification check, columns (3) and (4) repeat the above analysis on the part of the panel data before the listings are fully funded. The main effect of *Lag Total Amount* becomes insignificant, and the interaction terms exhibit no clear pattern. Therefore, herding does not seem to significantly influence interest rates before a listing is fully funded.

To summarize, in this section we start by documenting the fact that the amounts of funding a listing receives each day are sequentially correlated. We then establish evidence of herding after controlling for unobservable listing heterogeneity and payoff externalities among lenders. Furthermore, we find that lenders on Prosper engage in rational herding from the fact that listing attributes moderate the herding momentum. These findings are robust with respect to a set of alternative specifications.

[19] With data on friendship among Prosper lenders, one can extend this analysis to investigate whether friends' lending decisions impose a stronger social comparison effect. This issue will be an interesting topic for future research.

[20] The interaction between *Lag Average Amount* and *Lag Percent Needed* becomes negative, different from the main model. However, unlike cumulative funding, a larger average amount per bid does not necessarily increase the listing's chance of becoming a loan. Therefore, we do not expect a definitive sign on this interaction term.

4. Further Evidence of Rational Herding

In this section, we provide corroborating evidence of rational herding by restructuring the panel data and by using auxiliary data on Prosper.

4.1. Hourly Panel and First-Day Analysis

We have seen from column (6) of Table 5 that the effect of herding increases over the duration of a listing. If lenders who act on the first day of a listing tend to be more independent investors, then analyzing the first-day funding dynamics will provide a falsification check of the rational herding hypothesis. We expect these lenders to be less susceptible to their predecessors' decisions, let alone use listing attributes to fine-tune the interpretation of their predecessors' decisions.

For a finer-grained analysis of the first-day dynamics, we reconstruct the panel to use hourly intervals. However, to achieve a transparent comparison, we need to investigate funding dynamics at the hourly level over the entire listing duration as well. Moreover, a technical concern with the panel structure of the dataset is that it may cause dynamic panel biases in parameter estimates, whereas one way to reduce such biases is to enlarge the number of observation episodes for each listing (Arellano and Bond 1991). Therefore, estimating the model at the hourly level serves as an additional robustness check.

To avoid inflating the significance of estimates with a large sample size, we randomly select 5% of the listings from the daily panel, which results in an hourly sub-sample of 332,836 observations, comparable to the number of observations in the daily panel. Column (1) of Table 7 reports the estimation results of Equation (2) at the hourly level, controlling for payoff externalities. All variables remain significant and retain the same signs as their daily panel counterparts in column (2) of Table 4. The estimated main effect of *Lag Total Amount* is 0.009 at the hourly level, which is equivalent to $(1+0.009)^{24}-1=0.240$ at the daily level, comparable to the estimate of 0.256 obtained from the daily panel estimation. Column (2) estimates the main model of Equation (3) at the hourly level. Again, all variables retain the signs of their daily panel counterparts in column (4) of Table 4.

After ensuring that the hourly basis itself does not reveal different funding dynamics, we now focus on the first day of all listings in this hourly sub-sample. Columns (3) and (4) report the results, which differ noticeably from those of the daily panel. In particular, the main effect of *Lag Total Amount* becomes negative in column (3), and the interaction terms in column (4) indicate no clear pattern. These results suggest that first-day lenders are less reliant on herding and behave differently from what rational herding would predict. They may even avoid popular listings, perhaps because popularity might subsequently attract too many lenders to bid down the interest rate. These results on first-day lenders echo the findings of Agrawal, Catalini and

Table 7 Hourly Panel and First-Day Analysis

	(1) Entire Duration Herding	(2) Entire Duration Ratioanl Herding	(3) First Day Herding	(4) First Day Ratioanl Herding
Lag Total Amount	0.009 ***	0.144 ***	-0.208 ***	4.875 ***
	(0.001)	(0.014)	(0.006)	(0.194)
Lag Percent Needed (%)	-0.338 ***	-0.203 ***	-2.164 ***	-1.767 ***
	(0.023)	(0.029)	(0.179)	(0.238)
Lag Rate (%)	1.730 ***	1.851 ***	9.583 ***	6.161 ***
	(0.156)	(0.156)	(0.709)	(0.666)
Lag Total Bids	-0.693 ***	-0.046	-13.698 ***	-0.991 *
	(0.050)	(0.059)	(0.419)	(0.590)
Lag Total Amount * Lag Percent Needed (%)	3.9E-05 ***	3.0E-05 ***	-0.003 ***	-0.002 ***
	(7.4E-06)	(7.8E-06)	(4.8E-05)	(7.7E-05)
Lag Total Amount * Amount Requested (1,000)		0.001 ***		0.004 ***
		(2.7E-05)		(4.6E-04)
Lag Total Amount * Borrower Rate (%)		0.001 ***		-0.004 ***
		(2.5E-05)		(3.6E-04)
Lag Total Amount * Credit_Risky		0.010 ***		-0.240 ***
		(0.001)		(0.032)
Lag Total Amount * Debt-to-Income Ratio (%)		1.1E-04 ***		0.004 ***
		(4.2E-06)		(1.6E-04)
Lag Total Amount * Endorsements		-0.010 ***		-0.373 ***
		(0.001)		(0.011)
Lag Total Amount * Group Member		-0.008 ***		0.125 ***
		(3.6E-04)		(0.005)
Lag Total Amount * Homeowner		0.001 ***		-0.087 ***
		(2.8E-04)		(0.004)
Lag Total Amount * Lag Total Bids		-1.2E-05 ***		-1.3E-04 ***
		(1.3E-06)		(3.5E-05)
Lag Total Amount * Start Day		-9.9E-06 ***		-3.0E-04 ***
		(8.0E-07)		(1.1E-05)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Listing Fixed Effects	Yes	Yes	No	No
Listing Fixed Effects	Yes	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	332,836	332,836	52,451	52,451
Adjusted/Pseudo R-Squared	0.107	0.119	0.558	0.613

Notes: This table reports the estimation results of hourly panel analysis. The data include 5% of the listings from the daily panel. Columns (1)-(2) include the entire duration of these listings, and columns (3)-(4) include the first day. Each observation is a snapshot of a listing taken at the end of each hour. The dependent variable is the amount of funding a listing receives during an hour. GLS with standard errors clustered by listing and reported in parentheses under parameter estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Goldfarb (2011) that entrepreneurs' family and friends, who may have more information about the entrepreneurs, tend to invest early and are less susceptible to others' lending decisions.

4.2. Events that Shift the Informativeness of the Prosper Environment

Variations in the amount of information available on Prosper can provide another test of rational herding. Greater access to information reduces lenders' uncertainty about borrowers, thus weakening the need for herding. This effect may exist for both irrational and rational herding. However, the fact that early lenders made better-informed decisions enhances the information value of herding, thus strengthening the influence of the herd (Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992). This moderating role of information, similar to the moderating effects of listing attributes, is more relevant if herding is rational. Therefore, if greater availability of information is found to strengthen herding (in spite of the reduced need to herd), we can view it as further evidence of rational herding.

We identify four Prosper events during the time span of our data which might shift the informativeness of the lending environment. These events include technical updates to the Prosper website that provide better information transparency, and the annual "Prosper Days Community Conferences" for users to network and share their investment experiences:[21]

- August 9, 2006: "Renamed the 'MemberSince' field on the Member object to 'CreationDate' to be consistent with all the other objects. A 'LastModifiedDate' will be provided in the future."
- January 27, 2007: "Updated the 'Status' field to include more details on defaulted loans as well as repurchased loans."
- February 12-13, 2007: the first annual Prosper conference.
- February 25-26, 2008: the second annual Prosper conference.

The first event adds information about Prosper members and helps reduce lenders' uncertainty about a borrower (a Prosper member can be either a borrower or a lender). The second event allows lenders to access more information on loan performance, which helps lenders make better decisions by giving feedback on their past choices (e.g., Camerer and Ho 1999). The community conferences are "packed with knowledge-building sessions and networking opportunities" which allow lenders to learn from their successful peers, industry experts, and Prosper's top management.

To assess the impact of these events, we create four dummy variables: *Add Member Info*, *Add Default Info*, *Conference 1*, and *Conference 2*. Each variable equals 1 if a listing was posted after the corresponding event, and 0 otherwise. We then interact each event dummy variable with *Lag Total Amount* in the main model. (Similar to other listing attributes, the separate effect of these dummy variables cannot be identified from listing fixed effects.) Table 8 reports the results. All four event dummies have positive and significant interaction effects with *Lag Total Amount*, supporting the rational herding hypothesis.

4.3. Loan Performance and Herding

Unlike many field investigations of herding, studies of Prosper benefit from the opportunity to measure the actual quality of listings as manifested in subsequent loan performance. If herding is rational, well-funded borrowers should indeed be more creditworthy and less likely to default.

[21] Source: www.prosper.com. The website redesigns are driven by technical updates, and can be treated as exogenous shifters of website informativeness. The organization of community conferences might be endogenous. However, the *Start Day* variable helps capture any linear continuous change in the environment that has lead to the conferences; the dummy variables that mark the occurrence of the conferences reflect discrete shifts in information around these events. We also rerun the regressions using only observations that fall in the month before and the month after either conference. The interactions between *Lag Total Amount* and the conference dummies remain positive and significant.

Table 8 How Lenders' Access to Information Moderates Herding

	(1) Add Member Info	(2) Add Default Info	(3) Conference 1	(4) Conference 2
Lag Total Amount	1.773 ***	1.977 ***	2.700 ***	2.582 ***
	(0.109)	(0.127)	(0.130)	(0.151)
Lag Percent Needed (%)	-0.497 **	-0.460 *	-0.558 **	-0.373
	(0.242)	(0.242)	(0.242)	(0.242)
Lag Rate (%)	35.537 ***	35.629 ***	35.636 ***	35.707 ***
	(1.023)	(1.023)	(1.023)	(1.023)
Lag Total Bids	-1.938 ***	-1.560 ***	-1.391 ***	-1.554 ***
	(0.438)	(0.438)	(0.438)	(0.438)
Lag Total Amount * Lag Percent Needed (%)	0.002 ***	0.002 ***	0.003 ***	0.002 ***
	(6.0E-05)	(6.0E-05)	(6.0E-05)	(6.0E-05)
Lag Total Amount * Amount Requested (1,000)	0.019 ***	0.019 ***	0.019 ***	0.019 ***
	(2.1E-04)	(2.2E-04)	(2.2E-04)	(2.2E-04)
Lag Total Amount * Borrower Rate (%)	0.022 ***	0.022 ***	0.022 ***	0.022 ***
	(1.9E-04)	(1.9E-04)	(1.9E-04)	(1.9E-04)
Lag Total Amount * Credit_Risky	0.207 ***	0.212 ***	0.209 ***	0.216 ***
	(0.012)	(0.012)	(0.012)	(0.012)
Lag Total Amount * Debt-to-Income Ratio (%)	1.4E-04 ***	1.4E-04 ***	1.4E-04 ***	1.5E-04 ***
	(1.0E-05)	(1.0E-05)	(1.0E-05)	(1.0E-05)
Lag Total Amount * Endorsements	-0.111 ***	-0.113 ***	-0.116 ***	-0.110 ***
	(0.006)	(0.006)	(0.006)	(0.006)
Lag Total Amount * Group Member	-0.025 ***	-0.022 ***	-0.022 ***	-0.022 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Lag Total Amount * Homeowner	0.003	0.003	0.003	0.004 *
	(0.002)	(0.002)	(0.002)	(0.002)
Lag Total Amount * Lag Total Bids	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***
	(1.2E-05)	(1.2E-05)	(1.2E-05)	(1.2E-05)
Lag Total Amount * Start Day	-1.3E-04 ***	-1.4E-04 ***	-1.9E-04 ***	-1.8E-04 ***
	(6.5E-06)	(7.5E-06)	(7.7E-06)	(8.8E-06)
Lag Total Amount * Add Member Info	0.070 ***			
	(0.006)			
Lag Total Amount * Add Default Info		0.033 ***		
		(0.004)		
Lag Total Amount * Conference 1			0.064 ***	
			(0.004)	
Lag Total Amount * Conference 2				0.042 ***
				(0.004)
Day-of-Week Fixed Effects	Yes	Yes	Yes	Yes
Day-of-Listing Fixed Effects	Yes	Yes	Yes	Yes
Listing Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	347,851	347,851	347,851	347,851
Adjusted/Pseudo R-Squared	0.527	0.526	0.527	0.526

Notes: This table investigates how events that shift the informativeness of the Prosper environment affect herding. Each observation is a snapshot of a listing taken at the end of each day. The dependent variable is the amount of funding a listing receives during a day. GLS with standard errors clustered by listing and reported in parentheses under parameter estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For this follow-up study, we use an auxiliary dataset provided by Prosper, which reports the performance status of all loans from February 2006 to August 26, 2008. Out of the 6,102 fully funded listings from our panel data, 5,940 have corresponding loan performance records. We label a loan as "defaulted" if it has entered the status of bankruptcy or delinquency, or if payment is four or more months late, consistent with Prosper's policy of considering such loans as "eligible for debt sale." According to this definition, 359 or 6.05% of the loans had defaulted as of August 26, 2008.

Some loans in the sample had not reached maturity when the loan performance data were collected. To overcome this right-censoring problem, we estimate a Cox Proportional Hazard

(CPH) model of loan default rates. Now widely accepted in studying loan performances (e.g., Deng and Liu 2009), the CPH model relates the time that passes before default (if any) to loan covariates. We use the Kaplan-Meier approach to fit the empirical hazard rates. Table 9 presents the parameter estimates and associated hazard ratios.

Column (1) reports the association between loan attributes and default rates. A larger amount requested, higher borrower rate, risky credit, higher debt-to-income ratio, and fewer endorsements are all associated with a higher default rate. In other words, lenders have been correct in viewing these features as undesirable attributes that should strengthen the herding effect. Interestingly, borrowers who are group members are significantly more likely to default. Freedman and Jin (2008) also find that the estimated rate of return is lower for group loans. One explanation is that borrowers with higher credit risks tend to join Prosper groups but lenders are either unaware of or have underestimated this adverse selection problem. Borrowers' homeownership has a positive but insignificant relation with default rates, which again helps to explain why this listing attribute has a weak moderating effect on herding. Finally, loans initiated later in the sample are significantly less likely to default, consistent with the moderating effect of *Start Day* in the main model.

Table 9 Loan Attributes, Herding, and Performance

	(1) Loan Attributes and Default Rate		(2) Loan Attributes, Rational Herding and Default Rate		(3) Loan Attributes, Irrational Herding and Default Rate		(4) Loan Attributes, Rational vs Irrational Herding and Default Rate	
	Estimate	Hazard Ratio	Estimate	Hazard Ratio	Estimate	Hazard Ratio	Estimate	Hazard Ratio
Amount Requested (1,000)	0.056	1.058 ***	0.051	1.052 ***	0.054	1.056 ***	0.050	1.052 ***
	(0.004)		(0.004)		(0.004)		(0.004)	
Borrower Rate (%)	0.128	1.137 ***	0.128	1.136 ***	0.128	1.137 ***	0.128	1.136 ***
	(0.004)		(0.004)		(0.004)		(0.004)	
Credit_Risky (1=yes)	0.516	1.675 ***	0.440	1.553 ***	0.508	1.663 ***	0.441	1.554 ***
	(0.053)		(0.053)		(0.053)		(0.053)	
Debt-to-Income Ratio	0.055	1.056 ***	0.055	1.056 ***	0.054	1.055 ***	0.054	1.056 ***
	(0.015)		(0.016)		(0.015)		(0.016)	
Endorsements	-2.097	0.123 ***	-2.110	0.121 ***	-2.097	0.123 ***	-2.109	0.121 ***
	(0.377)		(0.378)		(0.377)		(0.378)	
Group Member (1=yes)	0.739	2.095 ***	0.743	2.103 ***	0.737	2.089 ***	0.742	2.099 ***
	(0.057)		(0.057)		(0.057)		(0.057)	
Homeowner (1=yes)	0.014	1.014	0.016	1.017	0.013	1.013	0.015	1.016
	(0.043)		(0.043)		(0.043)		(0.043)	
Start Day	-2.5E-04	1.000 *	-2.9E-04	1.000 **	-2.4E-04	1.000 *	-2.9E-04	1.000 **
	(1.4E-04)		(1.4E-04)		(1.4E-04)		(1.4E-04)	
Pct Funded (%) Rational Herding			-0.002	0.998 ***			-0.002	0.998 ***
			(2.2E-04)				(2.3E-04)	
Pct Funded (%) Irrational Herding					-1.1E-04	1.000 ***	-4.4E-05	1.000
					(3.3E-05)		(2.9E-05)	
Number of Observations	5,940		5,940		5,940		5,940	
-2 Log Likelihood	4,977.878		4,966.180		4,976.477		4,965.910	

Notes: This table reports the estimation results of Cox Proportional Hazard models for loan default rates. Default is defined as being in the status of bankruptcy or delinquency, or being four or more months late. Each observation is a loan. For each variable, we report the point estimate, the standard error in parentheses, and the hazard ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We test whether well-funded loans are less likely to default, after controlling for observable loan attributes. Since a listing might receive more funding simply because it has requested a larger amount independently of its quality, we use the normalized actual funding percentage (uncapped at 100%) as the independent variable.[22] Column (2) reports the results. All loan attributes exhibit similar effects as in column (1). The variable *Percent Funded (%) Rational Herding* turns out to be a significant indicator of loan performance. The hazard ratio suggests that each 1% increase in funding percentage is associated with a 0.2% decrease in loan default probability. This result echoes the finding of Herzenstein, Dholakia and Andrews (2011) that herding momentum on Prosper is positively associated with loan performance.

Next we test how irrational herding would have related to loan performance. To do so, we take a listing's first-day actual funding status as given, and use the parameter estimates from column (2) of Table 4 to recursively calculate the listing's funding amounts from day two to day seven.[23] This calculation yields the predicted funding amounts of an irrational herding model, which assumes that lenders ignore the moderating effects of listing attributes. We then normalize a listing's predicted funding amount by its requested amount, and call the resulting variable *Percent Funded (%) Irrational Herding*. Column (3) presents the results when we include this variable in the CPH model together with listing attributes. *Percent Funded (%) Irrational Herding* has a significant negative association with loan default rates, but its effect size is rather small. This result suggests that irrational herding may also contain information about borrower creditworthiness beyond what is captured by observed listing attributes. For example, it could be that early lenders have useful private information about the borrower. This information is then manifested in their funding decisions and repeatedly used by subsequent lenders in the irrational herd. However, this information could have been used more thoroughly had herding been rational.

To evaluate this last claim, we directly examine whether rational herding beats irrational herding in predicting loan default rates. We compare the two CPH models of columns (2) and (3) using the Vuong test (Vuong 1989). The model with rational herding explains loan defaults significantly better (Vuong test statistic $= 4.579$, $p < 0.01$). We also include both *Percent Funded (%) Rational Herding* and *Percent Funded (%) Irrational Herding* in the same model. As column (4) shows, irrational herding loses its explanatory power to rational herding. These results again highlight the importance of understanding the herding mechanism. By fitting a model assuming irrational herding, we might conclude that Prosper lenders make worse investment decisions than they actually do.

[22] We obtain the same qualitative conclusions if we adopt the total funding amount as the independent variable.

[23] While the progression of *Lag Percent Needed* is straightforward to compute, we rely on the empirical distribution to approximate the evolution of *Lag Rate* and *Lag Total Bids*—for each predicted funding amount, we look at the associated average rate and average bid count in our sample. This approach is admittedly a simplification compared with a lender-level structural forecasting model. Nevertheless, it allows us to qualitatively compare the powers of rational and irrational herding in explaining loan performance.

5. Concluding Remarks

Microloan markets differ from traditional bank-mediated credit markets in that each loan often relies on multiple lenders, peer lending behaviors are transparent, and each lender may face substantial uncertainty about the creditworthiness of a borrower. We find evidence of rational herding using a unique panel dataset from Prosper.com, the largest microloan market in the U.S. Lenders learn about the creditworthiness of a borrower from others' lending decisions in a sophisticated way. Counterintuitively, unfavorable listing attributes, such as high credit risks and high debt-to-income ratios, amplify the herding momentum, whereas favorable listing attributes, such as friend endorsements and group membership, weaken the herd. This happens as lenders rationally attribute a listing's herding momentum to its public attributes versus the borrower's intrinsic creditworthiness.

Given the ubiquitous presence of the herding phenomenon, it is important to understand the mechanism that drives herding. Knowing whether herding is rational would affect how accurately we can estimate the herding effect. Since rational observational learners interpret the herd relative to the choice context, if we spuriously assume irrational herding, we might underestimate the herding effect by ignoring adverse contextual elements, or overestimate it by omitting favorable contextual factors. Managerially, the degree of rationality behind herding critically affects strategies which aim to maneuver the herd. While efforts to accelerate the herd can attract an irrational following, they also dampen the quality signal of the herd in the eyes of rational observational learners.

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